Comparison of Randomly Undersampled MRI Reconstruction Methods

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Motivation

- Long scan time is one of the drawbacks of MRI
- **Compressed sensing (CS)** is widely used to reduce scan time
- Fewer data points are sampled in k-space (i.e., Fourier domain) which leads to artifacts in image
- **Random** undersampling pattern leads to **incoherent artifacts** that are difficult to be resolved

Related Work

- **Conjugate Gradient - SENSE** uses additional spatial encoding information from multi-coil array and conjugate gradient algorithm to iteratively to solve for the artifact reduced image [1] --> **Accurate coil sensitivity maps**
- **SPIRiT** recovers missing data points in k-space using their correlation with neighboring data. The weighting kernels are iteratively estimated and applied until stop criteria is met [2] --> **Calibration data needed for kernel estimation**
- ***l1* norm of sparse transform** of an image can be used with a data consistency constraint [3].
- **CNN based methods** are mainly concluded as two paradigms : 1) unrolling methods, e.g., ADMM-Net [4] and 2) end-to-end learning methods, e.g., MICCAN [5].

Dataset

Cardiac MR image dataset:

- Short-axis cardiac MR images
- Contains 3300 images in training set, 300 in validation set

MRNet dataset:

- Knee MR images in coronal view
- Contains 1478 images in training set, 145 in validation set

Brain tumor dataset:

- Brain MR images in axial view
- Contains 94 images in training set, 12 in validation set

References

[1] Pruessmann et al., Advances in Sensitivity Encoding With Arbitrary k-Space Trajectories, Magnetic Resonance in Medicine, 2001.
[2] Lustig et al., SPIRiT: Iterative Self-consistent Parallel Imaging Reconstruction From Arbitrary k-Space, Magnetic Resonance in Medicine, 2010.
[3] Lustig et al., Sparse MRI: The Application of Compressed Sensing for Rapid MR Imaging Michael, Magnetic Resonance in Medicine, 2007.
[4] Sun et al., Deep ADMM-Net for compressive sensing MRI. *Advances in neural information processing systems*, *29, 2016*
[5] Huang et al., MRI reconstruction via cascaded channel-wise attention network. *2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019)*. IEEE, 2019.
[6] Boyd et al, Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers, Foundation and Trends in Machine Learning, 2001.
[7] Rudin et al. Nonlinear total variation based noise removal algorithms, Physica D: Nonlinear Phenomena, 1992
[8]Qin et al., Convolutional recurrent neural networks for dynamic MR image reconstruction. *IEEE transactions on medical imaging* 38.1, 2018

Methods

- **Alternating Direction Methods of Multiplier (ADMM)** [6] to solve the constrained optimization problem:

$$\arg\min_x \frac{1}{2}||Ax-y||_2^2 + \lambda||Fx||_1$$

- Three priors: *l1* wavelet [3], Anisotropic and isotropic Total Variation (TV) [7]

$$TV_a(x) = \sum_{i=1}^{N} \sqrt{(D_x x)_i^2} + \sqrt{(D_y x)_i^2}$$

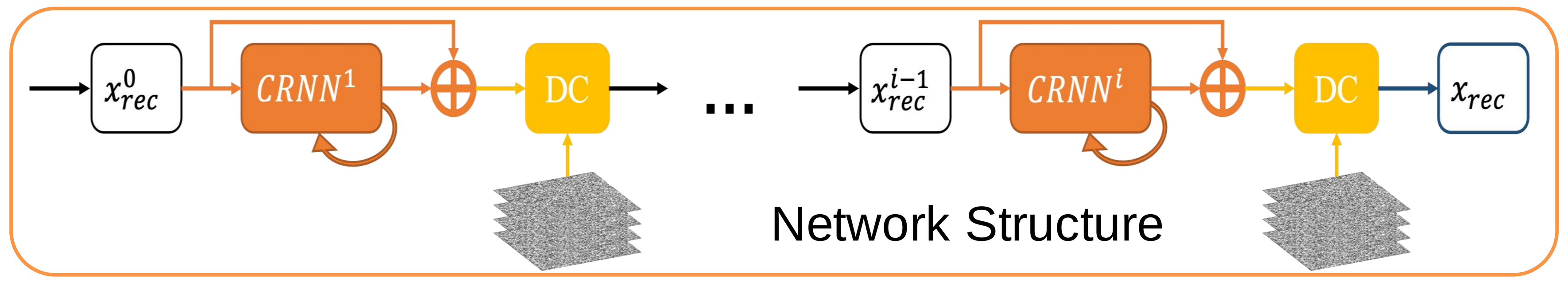
$$TV_i(x) = \sum_{i=1}^{N} \sqrt{(D_x x)_i^2 + (D_y x)_i^2}$$

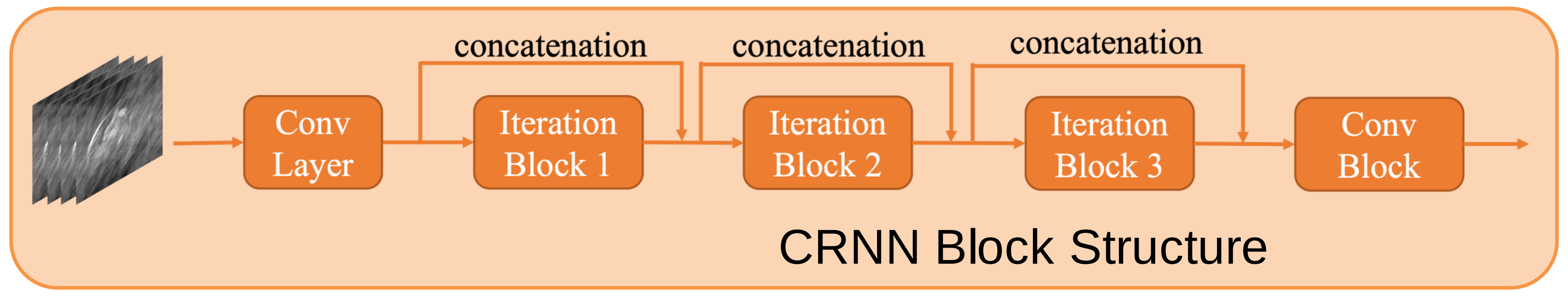
ADMM updated equations:

$$x^{k+1} := (A^T A + \rho F^T F)^{-1}(A^T b + \rho F^T (z^k - u^k))$$

$$z^{k+1} := S_{\lambda/\rho}(F x^{k+1} + u^k)$$

$$u^{k+1} := u^k + F x^{k+1} - z^{k+1}$$





Convolutional Recurrent Neural Network (CRNN) [8]

- Reconstructed output is described as

$$\tilde{x}_i = F_N(F_{N-1}(\dots(F_1(x_i, m_i; \theta_1)\dots); \theta_{N-1}); \theta_N)$$

x: undersampled image
m: corresponding mask
theta: network parameters

- Several recurrent blocks are used to simulate the iterative process of reconstruction.
- Iteration Blocks inside CRNN Block are combined with concatenation to obtain useful feature from previous steps.
- Residual connection could prevent the degradation problem.
- Data consistency layer is applied to enforce data fidelity.

Experimental Results

- Images are retrospectively undersampled in k-space with sampling rates 60% and 40%

Heart

	Zero filling	*l1* wavelet	TVa	TVi	CRNN
0.6	18.8	**30.5**	26.0	26.6	**44.2**
0.4	15.6	**25.9**	24.4	24.9	**37.4**

Brain

	Zero filling	*l1* wavelet	TVa	TVi	CRNN
0.6	18.6	**32.3**	30.0	29.9	**40.4**
0.4	15.5	**24.4**	23.7	23.8	**33.3**

- All methods can effectively reduce artifacts and improve PSNR
- CRNN produces results with highest PSNRs
- Among three priors, *l1* wavelet produces the best PSNRs but worse effects on removing artifacts
- TVi and TVa shows comparable PSNRs and artifact reduction, but results in contrast change